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Factors Influencing Intention to Adopt AI Chatbot in Civil Status and Passport Department in Jordan: The Moderating Role of Trust in Technology

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Abstract

This study investigates the determinants of chatbot adoption intention in Jordan's civil status and passport department, with a particular focus on technology trust as a moderating variable. Drawing on the Technology Acceptance Model (TAM), we developed and tested hypotheses regarding chatbot adoption factors. The research employed a quantitative approach, collecting data from 687 valid respondents out of 743 distributed questionnaires. Analysis using Smart-PLS software revealed that most examined factors positively influenced adoption intentions, with one notable exception: ease of use showed no significant impact on user attitudes. The findings confirmed that positive attitudes toward chatbots significantly enhanced adoption intentions, while trust in technology strengthened this attitude-intention relationship. This study extends existing theoretical frameworks by providing empirical evidence from a Middle Eastern context, specifically in Jordan's public sector, offering valuable insights for both researchers and practitioners implementing chatbot solutions in public services. The results particularly emphasize how trust in technology shapes user acceptance in the Jordanian context, contributing new perspectives to the current understanding of chatbot adoption dynamics.

Keywords: *Artificial Intelligence (AI), AI Chatbot, Anthropomorphism, Attitude, Electronic Word of Mouth, Perceived Interactivity, Perceived Technological Anxiety, Trust in Technology.*

Introduction

In the business environment, chatbots have the potential to revolutionize the business world, companies interact with their customers and work to improve the relationship with them (Darlington & Miebi Patience, 2023; labib 2024). It is known that chatbots are a computer

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program designed to conduct a human conversation via text messages over the Internet or via voice using text-to-speech conversion and exchange ideas or emotions that occur during conversations used by systems dedicated to chatbots to simulate human interaction (Ranieri et al., 2024; Alboqami 2023). Although chatbots have existed since the 1960s, they have witnessed tremendous developments at the present time, especially after the spread of the Covid 19 (Corona virus) in 2019 (Huang et al., 2024; Ranieri et al., 2024). Chatbots have become a popular tool for providing customer service in recent years due to the increasing demand for convenient and accessible customer service experiences by companies relying on chatbots as a means of providing 24/7 support and fast response times (Silva et al., 2024; Sobaih and Abu Elnasr 2025;).

While significant research has explored chatbot adoption in commercial settings, there remains a notable research gap regarding their implementation and acceptance in public services, particularly in Middle Eastern countries. Advances in artificial intelligence and natural language processing have enabled chatbots to understand and respond to customer inquiries more accurately and efficiently. They also serve as an engagement tool, such as promoting offers and coupons to multiple customers anywhere and at any time (Gupta et al., 2024; Apriani et al., 2024).

The recent emergence of Chatbot on November 30, 2022, has brought significant changes to the way individuals use the latest GenAI in their professions, especially in marketing (Awal & Haque, 2024). Chatbot is an example of an AI-powered tool that has the potential to revolutionize marketing capabilities (Gupta & Yang, 2024) by providing personalized recommendations, handling customer inquiries and complaints 24/7, attracting leads, helping create content, and analyzing customer data to provide insights into consumer behavior and preferences (Tiwari et al., 2023). However, despite these technological advances, understanding the factors that influence citizens' acceptance of chatbots in government services remains understudied, particularly in the context of Jordan's public sector.

The concept of Chatbot is a large language model and is one of the newly emerging AI technologies that can be used for engagement and marketing (Mousa et al., 2024). In terms of customer experience, Chatbot helps marketers provide personalized experiences for customers. Chatbot-powered chatbots can process and respond to customer inquiries in real-time, providing immediate customer response and enhancing customer experience (Gupta et al.,2024). Natural language processing is a vital component of designing consumer experiences using Chatbot. Chatbot can deliver a more engaging and human-like experience by using natural language processing to understand and respond to customer inquiries (Huong 2024; Pillai et al., 2024; Sobaih et al., 2025). Nevertheless, the role of trust in technology as a moderating factor in chatbot adoption, especially within government services, remains largely unexplored. This can reduce the workload on customer support teams, allowing them more time to focus on complex issues through Chatbot-powered conversation. This study addresses these research gaps by making three key contributions. First, it extends the Technology Acceptance Model by incorporating trust in technology as a moderating variable in the public sector context. Second, it provides empirical evidence from Jordan's civil status and passport department, offering insights into chatbot adoption in Middle Eastern public services. Third, it develops practical recommendations for government agencies implementing chatbot solutions.

A Chatbot-powered chatbot can answer a variety of questions, including customer service inquiries and the location of a customer’s luggage (Alshurideh et al., 2024). While marketers may use Chatbot to improve customer experiences, it is difficult to fully realize Chatbot’s potential without the relevance, personality, expertise, and personal connections that humans can provide (Tandon, 2023). Chatbot is used to build customer relationships and engage without any human input to destruction real customer relationships instead of increasing them. It is a huge development in artificial intelligence technologies, and it works on the possibility of repeating the processing of converting text to an image (Gupta et al., 2024; Awal & Haque., 2024) that AI product developers enhance the quality of chatbot software in terms of ease of use, while (Pilla et al., 2024) recommended adopting other factors and expanding the Technology Acceptance Model "TAM model**".** Considering these gaps and potential contributions**,** this study aims to identify the factors influencing users' intention to adopt the use of chatbot. The civil status and passport department in Jordan sector was chosen as the subject of the study. This research specifically addresses two key questions:

RQ1. Do the influencing factors have an impact on users' intention to adopt the use of Chatbot in Jordan's public services?

RQ2. To what extent does trust in technology moderates the relationship between attitude and intention to use Chatbot?

Theoretical Framework and Hypothesis Development

Intention to Adopt Chatbot

Intention refers to the tendency to interact with chatbot and make purchases, refer to future interactions and suggest them to customers (Nisha Pradeepa & Alam, 2024). The intention to adopt Chatbot is the most appropriate choice to explain the behavior of customers who intend to purchase a product and achieve prediction using this intelligence. Intention helps companies make marketing decisions related to demand for services, market segmentation and promotional strategies (Puertas et al., 2024; Behera et al., 2024). Actual use is a measure within the framework of the technology acceptance model, which reflects the individual's actual implementation and application of technology (Du & Lv, 2024).

Technology Acceptance Model (TAM)

With the rapid pace of new technological innovations, managers need to understand customer behavior related to technology acceptance and everything related to customers adopting or using these innovative technologies. At present, various theories are available that capture users' perceptions and attitudes about the attributes of innovative technology and predict the adoption of innovation by users (Pillai et al., 2024). It is suggested that the Technology Acceptance Model (TAM) can be useful in understanding the motivational factors that mostly influence behavior when it comes to it (Gupta & Yang, 2024). This is because the basic principle of TAM is that when people use different IT devices, they make rational decisions when using IT. With the increasing digitization, new technologies have emerged, Davis (1989) also developed a model as shown in Figure (2/1) (Awal & Haque, 2024). This study takes TAM into account to better understand customers' motivations for adopting chatbot in the Palestinian cellular sector, adding variables such as perceived technological anxiety, perceived interaction, electronic word of mouth, Anthropomorphism, trust in technology

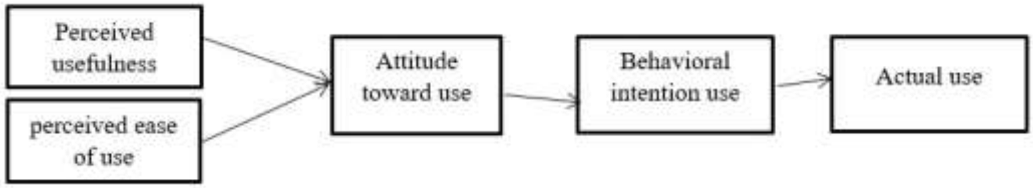

Figure 1. Technology Acceptance Model TAM

Source: (Davis et al., 1989)

Hypothesis Development

Perceived Usefulness (PEU)

Perceived usefulness is an important intrinsic predictor of intention to use Chatbot. When customers perceive chatbots as valuable and useful to meet their needs, they are more likely to express their intention to use them (Sobaih et. al, 2024; Mousa et al., 2024). Usefulness refers to the extent to which users believe that using an information system enhances their task performance (Cu Le 2024). The study by (Alshurideh et al., 2024; Almogren et al., 2024) revealed that usefulness has an impact on the intention to use Chatbot. The results of the study by (Silva, et al., 2024) indicated that usefulness has a positive impact on attitudes towards using chatbots. Usefulness is an important factor that predicts intentions to reuse chatbots. Considering this, we derive the following hypothesis:

H1: PEU has a positive impact on ATT

Perceived Ease of Use (PEOU)

Ease of use plays a crucial role in enhancing customer efficiency and productivity and is an important factor in influencing customer intention (Hoang & le tan, 2023). Ayanwale & Molefi, (2024) indicate that it is the degree to which a potential customer can expect and expect that using AI will require minimal effort and time. The study of Awal & Haque (2024) found that ease of use has no positive effect on behavioral intention to adopt chatbots. The same study found that ease of use negatively affects the intention to adopt AI-powered chatbots. Similar studies (e.g. Rahman et al., 2023; Hernandez et al., 2024; Tavakoli et al., 2023) showed that ease of use has a positive effect on attitudes to use AI. Additionally, other studies (Alshurideh et al., 2024; Almogren, et al.,2024) showed that ease of use has a positive effect on intention use chatbot. This leads us to the following hypothesis:

H2: PEOU has a positive impact on ATT

Perceived Technological Anxiety (PTA)

Technology anxiety refers to the degree to which consumers feel anxious about potential risks associated with the use of various modern technologies (Pillai et al., 2024). Anxiety is an important factor influencing consumers' intention to adopt chatbot (Cho & Seo, 2024). Anxiety is linked to the use of technology, and chatbot anxiety due to inaccurate information is fear or anxiety about being out of control or stressed due to unfamiliar trends in using chatbot (Sanusi et al., 2024). Studies (Alboqami 2023; Pillai & Sivathanu, 2020) revealed that technology anxiety has a negative impact on consumers' intentions, while study (Dekkal's 2023) showed that technology anxiety has a positive impact for less anxious users. From this, we derive the following hypothesis:

H3: PTA has a positive impact on ATT

Perceived Interactivity (PIT)

Interaction refers to the extent to which users can participate in modifying the model and content of a medium's environment in real time (Pillai et al., 2024). Interaction is positively associated with consumer satisfaction in this advanced digital age, and interaction plays a fundamental role in customer interactions with chatbots (Mousa et al., 2024). Recent studies (Auer et al., 2024; Awal & Haque, 2024; Le 2023) found that interaction has a positive effect on the intention to adopt chatbots. Considering this, we derive the following hypothesis:

H4: PIT has a positive impact on ATT

Anthropomorphism (ANM)

Anthropomorphism refers to the tendency of customers to attribute human traits and actions to inanimate objects such as chatbots and chatbot (Alboqami 2023). Anthropomorphism is known to convey a sense of competence by influencing customer behavior, as customers tend to feel more engaged and connected to the object (Nyagadza et al., 2022). Entrepreneurs believe that generative AI technologies may address their needs and solve problems in a similar way to those of humans. This affects their perception of the usefulness of the technology. The ability of technology to communicate with humans allows them to interact with it more instinctively and naturally (Gupta 2024). Increased analogy has a positive effect on perceived social presence and attitude, which are essential for meaningful human-computer interactions found that anthropomorphism had a positive effect on students' attitudes toward using chatGPT (Gupta, 2024; Polyportis & Pahos, 2024; Sobaih and Abu Elnasr, 2025). This leads us to formulate the following hypothesis:

H5: ANM has a positive impact on ATT

Electronic word of mouth (E-WOM)

It is a term used to describe any positive or negative comments about a company or product by potential, current or former customers that are shared online with a large audience (Elalfy et al., 2024; Mousa, et al., 2024). Electronic word of mouth has become an essential part of digital marketing by connecting companies and customers through the internet (Singh et al., 2024). Nowadays, electronic word of mouth requires a lot of physical networks and personal connections and uses digital platforms to enhance the communication process. Electronic word of mouth can appear across different online platforms such as websites, one-on-one messages, chats, communities, block lists, chat rooms, YouTube, and texts (Beyari & Garamoun 2024; Srivastava, et al., 2024; Tandon, 2023) found that electronic word of mouth has a positive effect on attitude. Awal & Haque (2024) found that word of mouth has a positive effect on the intention to adopt chatbots. From this we derive the following hypothesis:

H6: E-WOM has a positive impact on ATT

Attitude (ATT)

Attitudes towards use are defined as the process of shifting from the traditional method to the digital transformation using digital marketing services (Hernandez et al., 2024). Attitudes are not innately determined factors that do not change but can be changed through learning. These attitudes are related to factors such as personal belief, self-confidence, and self-expectations such as self-efficacy (Kim & Lee, 2024). Intention refers to the tendency to interact with chatbot and make purchases, and to refer to future interactions and suggest them to customers (Nisha Pradeepa & Alam, 2024). The intention to adopt the use of Chatbot is the most appropriate choice to explain the behavior of customers who intend to purchase a product and achieve prediction (Puertas, et al., 2024; Behera, et al., 2024). Recent studies (Polyportis and Pahos 2024; Almogren et al., 2024; Tiwari, et al., 2023 Pillai et al., 2024; Elshaer et al., 2024) found that attitudes have a positive effect on the intention to adopt the use of Chatbot. This leads us to formulate the following hypothesis:

H7: ATT has a positive impact on ADI

Trust in Technology

Trust in Technology is defined as the individual's willingness to accept the potential or risks associated with using technologies such as AI to achieve high-level outcomes. A particular technology or system will improve the performance of a job or task (Pitardi & Marriott, 2021; Behera, et al., 2024). Users' trust in technology is critical to its adoption and continued use. Users are more likely to adopt and use technology regularly if they perceive it as trustworthy (Ayanwale & Molef, 2024) and rely on their confidence in its reliability and dependability. Perceived trust in technology is expected to overcome users' skepticism that it is a reliable and trustworthy platform. As such, trust is a key component of successful technology adoption (Alifu et al., 2024). Malhotra Ramalingam, et al. (2023) found that trust moderates the relationship between perceived embodiment and perceived animacy, and (Chen et al., 2022) found that intelligence AI positively moderates the relationship between platform trust and customer engagement. A study (Pitardi & Marriott, 2021) revealed that trust towards voice assistants will have a positive impact on users' attitudes and intentions to use the technology. A study (Silva, et al., 2024) found that trust has a positive impact on attitudes towards using chatbots, while the importance of trust had no effect on repurchase intentions. This leads us to the following hypothesis:

H8: TRT in technology moderates the relationship between ATT and AIN

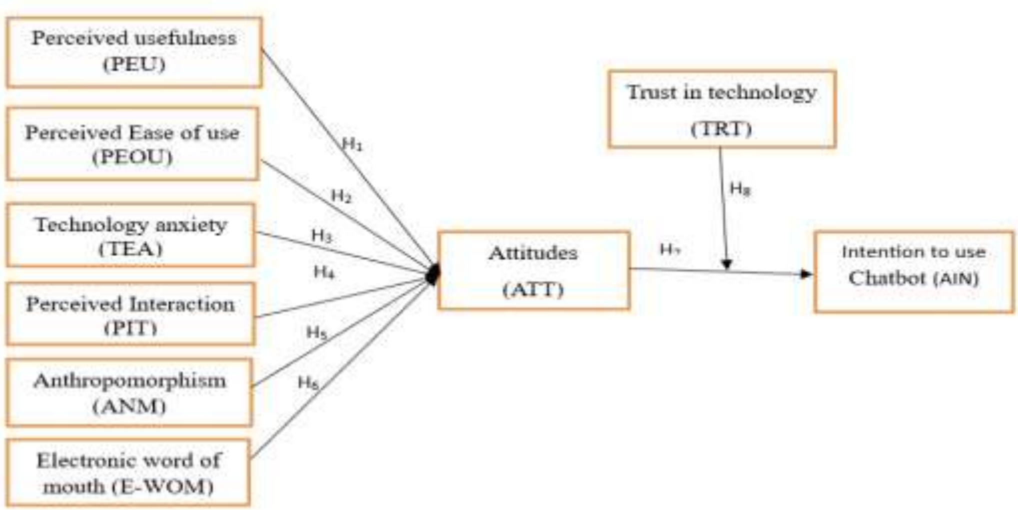

Figure 2. The Study Model (Prepared by the Researchers)

Methodology

The researchers utilized a descriptive and analytical approach, targeting a suitable sample of users from service recipients in the civil status department in Jordan. A total of 743 individuals were selected based on specific criteria. A structured questionnaire was used for data collection, and 687 valid responses were retrieved for statistical analysis.

Table 2 displays the frequencies and percentages of the demographic factors of the respondents. According to the demographic data, there is a balanced distribution of genders among the 737 persons that made up the analyzed sample. Out of a total of 387 people, 47.5% are male and 52.5% are female. This indicates that the sex ratio is about equal, with the females slightly outperforming the men. In terms of age distribution, the highest proportion of persons (336 out of 248) are in the 28 – 38-year-old bracket. The next largest age bracket, with 28.0% (206 people), consists of those aged 18 to less than 28 years. A quarter of the population, or 187 people, are in the 38–48 age bracket, while a thirteen percent share, or 96 people, are in the 48+ age bracket. This reveals a fairly even distribution of ages, with heavy concentration in the younger and middle-aged brackets. Regarding the level of education, 57.8% (426 people) of the sample had a bachelor's degree or above. At the same time, 23.5% (173 people) have gone on to get a master's or doctoral degree. Also, out of the total population, 13.4% (99 people) have a diploma, while 5.3% (39 people) have only completed high school. Most of the population has completed advanced degrees, according to this educational composition.

Of all the people who buy online, the biggest percentage (48.6%, or 358 people) spend between 16 and 30 hours each month doing so. Thirteen percent, or 232 people, spend eleven to fifteen hours a day in the second spot. Eleven percent, or 83 people, buy online at least once a month, while eight percent, or 64 people, spend more than 30 hours a month doing so. This suggests that most people participate in internet shopping to a moderate extent.

About 40.6% of the sample (299 people) had shopped online for 6–10 years, which is the longest duration of time for any given category. 222 people, or 30.1%, are next in line, followed by those with ten years of experience or more. Of the total, 22.4% (165 people) have between two and five years of experience, while 6.9% (51 people) have less than two years. This means that most people have shopped extensively online before. Of all the available payment methods, 44.5% (328 people) favor pay-on-delivery. The next most popular method of payment is credit cards, followed by debit cards with 11.9% acceptance (88 people). This shows that people favor quick and simple payment methods like credit cards and pay-on-delivery. Overall, the demographic data offers a thorough and inclusive analysis of the participants' attributes, including factors such as gender, age, education, hours spent on online shopping in a month, number of years of online shopping, and preferred mode of payment.

Demographic data	Frequency	%
Gender		
Male	350	47.5
Female	387	52.5
Age		
18- Less than 28 years	206	28.0
28- Less than 38 years	248	33.6
38- Less than 48 years	187	25.4
More than 48 years	96	13.0
Education		

High School and less	39	5.3
Diploma	99	13.4
Bachelor's degree	426	57.8
Higher studies	173	23.5
Hours spent online shopping in a month		
10 h	83	11.3
11–15 h	232	31.5
16–30 h	358	48.6
More than 30 h	64	8.7
Number of years of online shopping		
Less than 2 years	51	6.9
2–5 years	165	22.4
6–10 years	299	40.6
More than 10 years	222	30.1
Preferred mode of payment		
Pay-on-delivery	328	44.5
Credit card	321	43.6
Debit card	88	11.9

Table 2. Respondents' Demographics

Factor (criteria)	**Item No.**	**Item (questions)**	**Mean**	**SD**	**Factor Loading**	**α**	**CR**	**AVE**
PEU (Pillai, et al., 2024; Alboqami, 2023**)**	1	I can get answers to my inquiries more easily using Chatbot.	3.38	1.08	0.869	0.829	0.919	0.731
	2	Using Chatbot improves my performance.	3.33	0.95	0.776			
	3	I can get answers to my inquiries more effectively using Chatbot.	3.20	1.06	0.734			
	4	I find Chatbot useful in call centers.	3.19	1.07	0.757			
	5	I find using Chatbot more beneficial than traditional services.	3.17	1.15	0.815			
PEOU (Silva, et al., 2024; Alboqami, 2023)	6	Learning to use Chatbot will be easy for me.	3.25	1.33	0.849	0.870	0.786	0.710
	7	I find it easy to get Chatbot to do what I want them to do.	3.08	1.22	0.798			

Factor (criteria)	**Item No.**	**Item (questions)**	**Mean**	**SD**	**Factor Loading**	**α**	**CR**	**AVE**
	8	It will be easy for me to become skilled with Chatbot.	3.15	1.13	0.776			
	9	It is easy for me to become proficient in using Chatbot.	2.93	1.21	0.744			
	10	I think the language used in Chatbot is clear and easy.	3.30	0.98	0.813			
TEA (Pillai, et al., 2024; Alboqami, 2023)	11	I avoid advanced technological uses, such as Chatbot.	3.02	1.23	0.790	0.855	0.705	0.712
	12	I avoid using Chatbot because they are unfamiliar to me.	3.01	1.27	0.860			
	13	I find it difficult to understand communication with Chatbot.	3.01	1.27	0.808			
	14	I am unable to adapt to advanced technologies such as Chatbot.	3.84	1.02	0.700			
	15	I might encounter a problem while communicating with Chatbot.	3.06	1.13	0.723			
PIT (Pillai, et al., 2024)	16	My interaction with the Chatbot will be flexible.	3.28	1.15	0.764	0.868	0.926	0.785
	17	My interaction with the Chatbot will be clear and understandable.	3.37	1.08	0.836			
	18	Chatbot conduct interactive conversations with users.	3.51	1.03	0.835			
	19	Unlike traditional shopping apps and websites...	3.27	1.04	0.874			

Factor (criteria)	Item No.	Item (questions)	Mean	SD	Factor Loading	α	CR	AVE
	20	Chatbot achieve the interactivity of personal communications.	3.29	1.12	0.761			
ANM (Pillai, et al., 2024; Alboqami, 2023)	21	Chatbot for shopping have their own mind.	3.29	1.15	0.763	0.874	0.776	0.714
	22	Chatbot for shopping can experience emotions.	3.51	1.03	0.772			
	23	Conversations with Chatbot should be natural.	3.26	1.05	0.713			
	24	Chatbot seem to understand the person they interact with.	3.50	1.04	0.716			
	25	Conversations with a chatbot should not be artificial.	3.28	1.12	0.784			
E-WOM (Tando,2022; Mousa, et al.,2024)	26	E-WOM generates a good impression of Chatbot use.	3.28	1.14	0.771	0.810	0.813	0.726
	27	E-WOM publications are constantly updating.	3.37	1.08	0.839			
	28	E-WOM information is of high content.	3.51	1.03	0.845			
	29	E-WOM generates a good impression of Chatbot use.	3.25	1.05	0.867			
	30	Word of mouth makes me hesitant to use Chatbot.	3.28	1.12	0.768			
ATT (Pillai, et al., 2024;Tandon,2022)	31	Using Chatbot is a positive experience for me.	3.38	1.08	0.771	0.811	0.816	0.841
	32	For me, using Chatbot is enjoyable.	3.33	0.95	0.839			
	33	Using Chatbot is a good idea.	3.21	1.06	0.845			

Factor (criteria)	**Item No.**	**Item (questions)**	**Mean**	**SD**	**Factor Loading**	**α**	**CR**	**AVE**
	34	Chatbot adds value to my website and emotional balance.	3.19	1.07	0.867			
	35	I am enthusiastic about using Chatbot.	3.17	1.15	0.768			
TRT (Alboqami, 2023; Pillai, et al., 2024)	36	AI maintains confidentiality of personal info.	3.37	1.08	0.835	0.778	0.780	0.818
	37	Privacy is well protected by AI use.	3.33	0.95	0.874			
	38	AI use meets my expectations.	3.17	1.08	0.761			
	39	AI enables me to do what I need.	3.18	1.06	0.763			
	40	My tendency to rely on AI is high.	3.15	1.15	0.772			
AINA (lboqami, 2023 Tandon,2022)	41	Chatbot meets my needs and desires.	3.24	1.33	0.839	0.876	0.879	0.671
	42	My interest in Chatbot use will increase.	3.08	1.22	0.845			
	43	Using Chatbot is a wise idea.	3.15	1.13	0.867			
	44	I will use Chatbot when I encounter them.	2.92	1.20	0.768			
	45	I will recommend others to use Chatbot.	3.29	0.99	0.835			

Table 3. Measurement model

Measurement Model Evaluation

This model is a part of the structural equation model that deals with variables under research, their indicators and the relationships between these variables. It also describes the validity and reliability of the model. The factor loading is the association degree of each variable with each factor. Thus, factor loading validity test assesses the validity of each field individually as well as the validity of the questionnaire. The test computes the factor loadings between one field and every field of the same level in the questionnaire. Factor loading values should be more than 0.7 to be accepted (Hair et al. 2019). Table 3. shows the Measurement model values.

The Average Variance Extracted (AVE) purpose is to assess each validity's construct and the latent variable. If the AVE value is more than 0.5, the variable is valid and meet the conditions (Hair et al. 2019). Table 4.9 shows the AVE values which equal or more than 0.5, and this clarifies that the variables are valid. The composite reliability coefficient (CR) and Cronbach's coefficient α (CA) were used to assess internal consistency. The objective of Cronbach's alpha is to increase the composite reliability outcomes for a variable. According to Hair et al. (2019) and Pallant (2020), a variable is considered acceptable if Cronbach's alpha value is higher than 0.7. The range of the Cronbach's coefficient alpha value, according to Fellows and Liu (2008), is between 0.0 and + 1.0, with higher values suggesting a higher level of internal consistency. Therefore, Cronbach Alpha and the significance level were used to confirm the study's findings and assess the validity of the questions. Cronbach's Alpha values for each questionnaire field as well as the total questionnaire are displayed in Table (4.9). The Cronbach's Alpha scores for the fields fell between values 0.778 to 0.876, which is above the necessary 0.70 value (acceptable) and above the value of 0.70 (preferred) (Pallant, 2020). It can be concluded that the researcher demonstrated the validity and reliability of the questionnaire which is examined by using (PLS-SEM V4) and every questionnaire field's alpha Cronbach's coefficient was determined. Furthermore, to verify the constructions' dependability, the CR value was further calculated. The findings demonstrate that every CR value is higher than 0.7. According to the CR results, the model's degree of dependability is deemed satisfactory (Chin, 2010; Hair et al., 2019).

Hair et al. (2019) noted that by using this method, the correlation of latent constructs is compared with the square root of (AVE). Rather than clarifying the variance of other latent constructs, a latent construct should be better able to explain the variance of its own indicator so the square root of each construct's AVE should be larger than the association with other latent constructs. The findings demonstrate that any value at the diagonal is bigger than a value that is not diagonal, indicating that there is no problem with the model's discriminant validity. Table (4) displays these criterion's findings.

	1. PEU	2. PEOU	3. PTA	4. PIT	5. EWOM	6. ANM	7. ATT	8. TRT	9. AIN
1. PEU	0.855								
2. PEOU	0.491	0.843							
3. PTA	0.518	0.660	0.844						
4. PIT	0.425	0.708	0.641	0.886					
5. E-WOM	-0.017	-0.066	0.041	0.005	0.923				
6. ANM	-0.015	-0.054	-0.028	0.089	0.401	0.852			
7. ATT	0.024	-0.108	-0.085	0.082	0.425	0.731	0.917		
8. TRT	0.105	-0.010	-0.018	-0.034	0.039	-0.035	0.019	0.905	

9. AIN	0.016	-0.040	-0.010	-0.027	0.128	0.188	0.105	0.355	0.852

Table 4. Fornell-Larcker Correlations

Determination coefficient analyzes the degree of accuracy of the external construct predictions (Pasaribu et al. 2022), which means the degree of variance in the endogenous (dependent) variables because of the exogenous (independent) variables in the structural model. When the value of (R^2) the values below 0.33 are considered weak, while values between 0.33 and 0.67 are considered moderate, more than 0.67, it’s considered high, (Chin, 2010).

The Results

Relationships between different dimensions and Attitudes (ATT) of Intention to use Chatbot (AIN) are shown by the structural estimates in Table 5.

	Construct	**Standard Beta (β)**	**Standard Deviation (STDEV)**	**T Statistics (|β /STDEV|)**	**P Values**	**2.5%**	**97.5%**	**Result**
H1	PEU -> ATT	0.087	0.046	2.400	0.016	-0.017	0.164	Supported
H2	PEOU -> ATT	-0.109	0.083	1.707	0.088	-0.211	0.118	Not Supported
H3	PTA -> ATT	-0.126	0.061	2.414	0.016	-0.217	0.065	Supported
H4	PIT -> ATT	0.137	0.064	2.720	0.007	-0.031	0.226	Supported
H5	E-WOM -> ATT	0.167	0.032	5.208	0.000	0.104	0.229	Supported
H6	ANM -> ATT	0.639	0.028	22.924	0.000	0.584	0.694	Supported
H7	ATT -> AIN	0.113	0.035	3.191	0.001	0.042	0.182	Supported
H8	TRT -> AIN	0.356	0.039	9.046	0.000	0.279	0.432	Supported

Table 5: Structural estimates: path coefficients

In order to determine the effect on attitudes (ATT) and Intention to use Chatbot (AIN), the study looks at the connections between different components. The path coefficients (β), standard deviations (STDEV), T-statistics, P-values, and 95% confidence intervals (2.5% and 97.5%), together with other statistical measures, compose the findings. We assess the hypotheses using the statistical significance of the associations at the 0.05 level.

H1: Perceived usefulness (PEU) → Attitudes (ATT)

There was a statistically significant correlation between ATT and PEU, or perceived ease of use. 0.087, 2.400, and 0.016, respectively, demonstrated the positive impact. Between -0.017 and 0.164, the 95% confidence interval for β fell. The P-value is less than 0.05 and the confidence interval excludes zero, thereby supporting this hypothesis.

H2: Perceived Ease of use (PEOU) → Attitudes (ATT)

The results showed that there was no significant association between attitudes (ATT) and perceived ease of use (PEOU), with β = -0.109, T = 1.707, and P = 0.088. The 95% confidence interval was non-zero, falling between -0.211 and 0.118. No evidence supports the theory, suggesting no meaningful association.

H3: The Technology anxiety (TEA) → Attitudes (ATT)

With β = -0.126, T = 2.414, and P = 0.016, there was a significant connection between perceived technology acceptance (PTA) and attitude toward usage (ATT). Between -0.217 and 0.065, the confidence interval fell. The data confirms this inverse correlation, as the confidence interval stays below zero and the p-value is less than 0.05.

H4: Perceived Interaction (PIT)→ Attitudes (ATT)

With β = 0.137, T = 2.720, and P = 0.007, there was a significant association between attitudes (ATT) and personal interaction (PIT). An interval of -0.031 to 0.226 was the 95% confidence interval was between -0.031 and 0.226. The P-value, demonstrating statistical significance, supports the hypothesis even when the lower limit is almost zero.

H5: Electronic word of mouth (E-WOM) → Attitudes (ATT)

With β = 0.167, T = 5.208, and P < 0.001, Electronic word of mouth (EWOM) significantly and positively affected attitudes (ATT). The 95% confidence interval did not go beyond 0.229, with a range of 0.104. All signs point to the theory being correct.

H6: provides an explanation of the Anthropomorphism (ANM) → Attitudes (ATT)

With β = 0.639, T = 22.924, and P < 0.001, Anthropomorphism (ANM) had the most significant beneficial effect on attitudes (ATT). The 95% confidence interval, spanning from 0.584 to 0.694, demonstrated a substantial and very significant impact. There is much evidence to back up this theory.

H7: Attitudes (ATT)→ Intention to use Chatbot (AIN)

The attitudes (ATT) significantly impacted the Intention to use Chatbot (AIN), according to the в-value (0.113), T-value (3.191), and P-value (0.001). Statistical analysis revealed a positive and statistically significant connection, with a confidence interval ranging from 0.042 to 0.182. As a result, this theory has merit.

H8: Trust in technology (TRT) → of Intention to use Chatbot (AIN).

With H = 0.356, T = 9.046, and P < 0.001, Trust in technology (TRT) significantly and positively impacted the intention to use Chatbot (AIN). The 95% confidence interval, spanning from 0.279 to 0.432, confirmed strong support for the hypothesis.

The results confirmed the majority of the hypotheses, demonstrating substantial connections between the components and either attitudes or intention to use Chatbot. There was insufficient evidence to support other associations, including those involving attitude and perceived ease of use or the link between attitudes and trust in technology. These findings shed light on the model's constituent parts that affect user sentiment and adoption intentions.

According to Baron and Kenny (1986), a mediator is a third variable that indicates how the independent variable affects the dependent variables. It is crucial to remember that a prior analysis of the direct association between mediating role of Strategic Intelligence in the impact of Competitive Advantage. The technique of PLS-SEM was used for assessing this relationship (Figure 3).

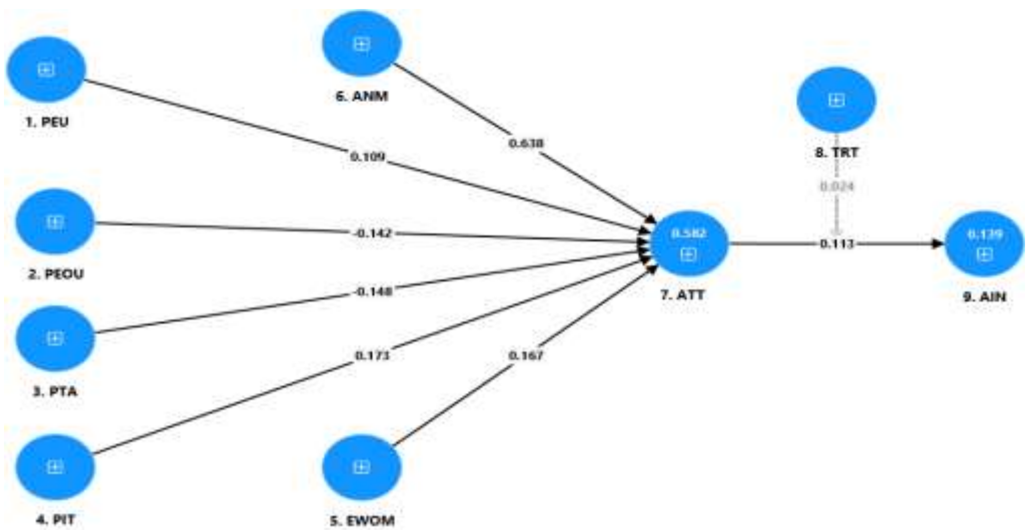

Figure 3: Structure model for the mediating Competitive Advantage

Trust in technology (TRT) mediates the relationship between Attitudes (ATT) and Intention to use Chatbot (AIN) (Table 6).

	Construct	**Standard Beta (β)**	**Standard Deviation (STDEV)**	**T Statistics (|β /STDEV|)**	**P Values**	**2.5 %**	**97.5 %**	**Result**
H1b	PEU -> ATT -> AIN	0.010	0.006	2.052	0.040	-0.002	0.022	Supported
H2b	PEOU -> ATT -> AIN	-0.012	0.010	1.579	0.114	-0.028	0.013	Not Supported

H3b	TEA -> ATT -> AIN	-0.014	0.008	2.030	0.042	-0.030	0.006	Supported
H4b	PIT -> ATT -> AIN	0.015	0.009	2.285	0.022	-0.003	0.031	Supported
H5b	ANM -> ATT -> AIN	0.072	0.024	3.042	0.002	0.027	0.120	Supported
H6b	EWOM -> ATT -> AIN	0.019	0.006	2.955	0.003	0.007	0.032	Supported

Table 6: Structural Estimates: Specific Indirect Effects

This paper examines the particular indirect effects, focusing on the association between components and their indirect influence on Intention to use Chatbot (AIN) via Attitudes (ATT) as moderate. In this study, the path coefficients (β), statistical measures of variability (STDEV), T-statistics, P-values, and the 95% confidence intervals (2.5% and 97.5%) are all looked at. When the P-value is less than 0.05 and the confidence interval does not intersect zero, we deem the hypotheses supported.

H 1b: Perceived Usefulness (PEU) → Attitudes (ATT) → Intention To Use Chatbot (AIN

We observe a statistically significant indirect influence of (PEU) via (ATT) on (AIN). We report as shown by β = 0.010, a T value of 2.052, and a P value of 0.040. The confidence interval spans from -0.002 to 0.022 (inclusive). The hypothesis confirms that PEU indirectly has a positive causal effect on AIN through ATT, despite the bottom limit being near zero.

H 2b: Perceived Ease of Use (PEOU) → Attitudes (ATT) → Intention to Use Chatbot (AIN)

According to the statistics, there isn't a strong link between perceived ease of use (PEOU) and Intention to use Chatbot (AIN) through Attitudes (ATT), as shown by β = -0.012, T = 1.579, and P = 0.114. A confidence interval spanning from -0.028 to 0.013 intersects zero. These findings show no significant indirect impact and do not support the hypothesis.

H3b: Technology anxiety (TEA) → Attitudes (ATT) → Intention to use Chatbot (AIN)

The statistical analysis reveals that perceived Technology anxiety (TEA) has a negative and statistically significant indirect influence on Intention to use Chatbot (AIN) via Attitudes (ATT). The coefficients calculated are β = -0.014, T = 2.030, and P = 0.042. The confidence interval spans from -0.030 to 0.006 (inclusive). Given that the P-value is less than 0.05 and the confidence interval remains above zero, we may conclude that there is supportive evidence for this negative indirect impact.

H4b: Perceived Interaction (PIT)→ Attitudes (ATT) → Intention to use Chatbot (AIN)

Perceived Interaction (PIT) has a statistically significant and positive indirect impact on the Intention to use Chatbot (AIN) via Attitudes (ATT). The obtained values are β = 0.015, T = 2.285, and P = 0.022. We observe that the confidence interval ranges from -0.003 to 0.031. The hypothesis indeed supports a favorable indirect impact of PIT on AIN via ATT, despite the lowest limit being close to zero.

H5b: Anthropomorphism (ANM) → Attitudes (ATT) → Intention to use Chatbot (AIN)

The statistical significance of the indirect link between Anthropomorphism (ANM) and Intention to use Chatbot (AIN) via Attitudes (ATT) is shown to be $\beta = 0.072$, $T = 3.042$, and $P = 0.002$. The calculated confidence interval spans from 0.027 to 0.120, suggesting a robust positive indirect impact. These findings provide robust support for this concept.

H6b: Electronic word of mouth (E-WOM) → Attitudes (ATT) → Intention to use Chatbot (AIN) .

The statistical analysis reveals a substantial and favorable indirect impact on Intention to use Chatbot (AIN) via Attitudes (ATT). The standardized beta coefficient is 0.019, with a T-value of 2.955 and a P-value of 0.003. The confidence interval, which spans from 0.007 to 0.032, provides robust evidence in backing this hypothesis . The research confirms the validity of most specific indirect effects. The Attitudes mediates the positive indirect effects of Intention to use Chatbot (AIN). Therefore, we can assert that trust in technology (TRT) neither strengthens nor weakens the relationship between attitudes and Intention to use Chatbot (AIN).

Discussion of the Results

The study investigated the main factors influencing users' intention to adoption the use of chatbot in civil status and passport Department in Jordan. This research provides valuable insights into the digitalization of public services in Jordan, particularly highlighting the complexity of technology adoption in government institutions. The empirical analysis revealed several key findings that contribute to our understanding of chatbot adoption in the public sector context. In addition, the moderating role of trust in technology factor influencing the relationships of attitude and intention to use chatbot. The results indicated a strong interest among the research sample in factors affecting users intention to adopt Chatbot, except for perceived ease of use (PEOU). This unexpected finding regarding PEOU suggests that Jordanian citizens may prioritize functionality and utility over ease of use when interacting with government services.

The study concluded that PEU positively influences attitudes (ATT), consistent with the findings of studies (e.g. Alshurideh et al., 2024; Almogren et al., 2024; Silva et al. , 2024). This reinforces the importance of demonstrating clear utility benefits to citizens when implementing chatbot solutions in public services. However, PEOU was also shown to have a direct positive impact on ATT, aligning with research (e.g. Rahman et al., 2023; Awal & Haque., 2024; Hernande et al., 2024). Interestingly, the study also demonstrated that (PTA) positively affects ATT, aligning with previous works (Auer et al., 2024 Bangladesh & Haque., 2024). This suggests that a certain level of technological anxiety might encourage users to develop more positive attitudes towards chatbots, possibly due to increased engagement with the technology.

Conversely, findings regarding perceived anxiety (ANM) and electronic word-of-mouth (E-WOM) showed positive impacts on ATT, consistent with previous research (Pahos & Polyportis, 2024; Gupta, 2024). The strong influence of E-WOM highlights the crucial role of social influence in technology adoption within the Jordanian cultural context, where social recommendations carry significant weight in decision-making processes. A particularly noteworthy finding is that the study confirmed that trust in technology moderates the relationship between ATT and the intention to adopt (AIN), corroborating studies (Silva et al.,2024; Pitardi & Marriott, 2021, Sobaih and Abu Elnasr 2025). This moderating effect underscores the critical importance of building and maintaining trust in public technological implementations, especially in contexts where citizens might be initially hesitant to adopt new digital services.

Limitations Study and Future Research

Our study presents several limitations that provide opportunities for future research. Regarding sampling, it would be beneficial to expand the number of respondents to better represent both public and private sectors. Methodological constraints also include the cross-sectional nature of the data and the need for a more balanced distribution of respondents across sectors. Future studies could explore the indirect impact of social demographic variables such as income and occupation which is an important element as it allows for more comprehensive implications for all departments, agencies and ministries. Furthermore, while our focus on the civil status and passport department provided specific insights, certain factors influencing chatbot adoption intention might not have been captured. To address these limitations, future researchers can follow up the current research to improve the ways to implement chatbot in various fields, with emphasis on conducting longitudinal studies to track changes in adoption behavior, providing a more comprehensive understanding of the variables involved and their impact on organizational performance. It would also be relevant to examine the effectiveness of different policy interventions aimed at promoting chatbot adoption across both sectors, as well as observe the influence of other factors such as market competition, industry regulations, and global technological trends on chatbot adoption behavior in both public and private sectors in Jordan.

Research Implications

Theoretical Implication

This research makes several significant theoretical contributions to the existing literature. The study contributes to the existing body of knowledge on the Technology Acceptance Model (TAM) and the other theories of Acceptance and Technology Use, by applying and testing these frameworks in the unique context of the most government service departments, such as, civil status and passport department in Jordan. Specifically, our findings extend TAM in three ways: first, by validating its applicability in the Middle Eastern public sector context; second, by incorporating novel variables such as technological anxiety and anthropomorphism; and third, by demonstrating the critical role of trust as a moderating factor in technology adoption. This study also provides insights into the factors influencing users' intention to adoption the use of chatbot adoption among civil status and passport department in Jordan, which can be useful for future research in this area. Our results particularly highlight the interconnected nature of technological, psychological, and social factors in shaping adoption intentions within government services. Moreover, the current study highlights the importance of the role that trust in technology is played as a moderating factor, offering a more nuanced understanding of how trust mechanisms operate in public transformations.

Practical Implications

Our findings offer several actionable insights for practitioners and policymakers. With the help of study findings, the policymakers whether in the public or private sector, and to work in partnership between them to benefit from the variables of this study and apply it to all departments, agencies and ministries. This cross-sectoral collaboration is particularly crucial for ensuring consistent digital service delivery across different government entities. Also, small, medium and large business owners can use the results of this study to realize the factors affecting users / customers intention to adoption on and make up-to-date decisions regarding the adoption of chatbot technologies in their business companies. The identified success factors can serve as a roadmap for organizations planning to implement chatbot solutions, helping them anticipate and address potential adoption barriers. Moreover, the public and private sectors can use the study results to develop and market to find solutions to facilitate transaction procedures, especially after official working hours, weekend and holydays in Jordan. This temporal flexibility offered by chatbots represents a significant opportunity to enhance service accessibility and citizen satisfaction, particularly during non-traditional working hours. Additionally, our findings suggest that organizations should focus on building trust through transparent communication about chatbot capabilities and limitations, develop strategies to address technological anxiety among users, leverage positive word-of-mouth through early adopters and success stories, and design implementation strategies that consider both functional utility and ease of use.

Recommendations

Based on our empirical findings, we propose the following comprehensive recommendations for both practitioners and policymakers:

1) Develop a comprehensive digital transformation strategy with clear, time-bound plans for AI integration across all departments, agencies and ministries in both sectors.
2) Enhance users' technological capabilities through targeted training programs and user-friendly support materials to improve chatbot adoption rates.
3) Establish intensive training programs for employees to develop their AI competencies and ensure effective chatbot management and support.
4) Implement a robust feedback system to continuously monitor, evaluate, and improve chatbot performance based on user experiences.
5) Create a multi-disciplinary team involving AI experts and service providers to optimize chatbot functionality and integration within existing systems.
6) Develop clear performance metrics and KPIs to measure the effectiveness and impact of chatbot implementation.
7) Design and implement a user-centric chatbot interface that prioritizes both ease of use and service efficiency.
8) Establish a dedicated support system for handling technical issues and user inquiries related to chatbot services.
9) Regular review and update of chatbot capabilities to keep pace with technological advancements and evolving user needs.

These recommendations aim to ensure successful chatbot implementation while maximizing user adoption and satisfaction across public services.

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